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Exploring the impact of mobility restrictions on the COVID-19 spreading through an agent-based approach

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A B S T R A C T

Background: The recent health emergency caused by the COVID-19 pandemic forced people to change their mobility habits, with the reduction of non-essential travels and the promotion online activities. During the first phase of the emergency in 2020, governments considered several mobility restrictions to avoid the pandemic diffusion. However, it is difficult to quantify the actual effects of these restrictions on the virus spreading, especially due to the biased data available. Notwithstanding the big role of data analysis to understand the pandemic phenomenon, it is also important to have more general models capable of predicting the impact of different policy scenarios, including territorial parameters, independently from the available infection data. In this respect, this paper proposes an agent-based model to simulate the impact of mobility restrictions on the spreading of the COVID-19 at a large scale level, by considering different factors that can be attributed to the diffusion and lethality of the virus and population mobility patterns.
Methods: The first step of the method includes a zonation of the study area, according to administrative boundaries. A risk index is calculated for each zone considering indicators which can influence the virus spreading and people lethality: mean winter temperature, housing concentration, healthcare density, population mobility, air pollution and the percentage of population over 60 years old. The agent-based model associates the risk index to the agents and determines their "status" ("susceptible", "infected", "isolated", "recovered" or "dead") by combining the risk index with the mean infection duration, using a SIR-based approach (i.e. susceptible–infective-removed).
Results: The study is applied to Italy. Several scenarios based on different mobility restrictions have been simulated, including the one based on the official data (*status quo*). The main results show that characterizing zones with a risk index allows to adopt local policies with almost the same effectiveness as in the case of restrictions extended to the full study area; scenario simulations return an increase in terms of infected (+20%) and deaths (+25%) with respect to the *status quo*. These results underline the importance of finding a trade-off between socio-economic benefits and health impact.
Conclusions: The reproducibility of the proposed methodology and its scalability allow to apply it to different contexts and at a different administrative level, from the urban scale to a national one. Moreover, the model is able to provide a decision-support tool for the design of strategic plans to contrast pandemics based on respiratory diseases.

1. Introduction

The recent health emergency caused by the COVID-19 pandemic has forced people to change their mobility behaviours, with the reduction of leisure travels and the promotion of teleworking and online educational activities (De Vos, 2020). Among the most applied

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contagion control measures, those relating to the limitation of travels, e.g. the so-called “stay-at-home” order, have become widespread with the aim of avoiding the circulation of the virus in public environments. Public transport has been highly impacted both by government restrictions and travellers’ choices (Jenelius and Cebecauer, 2020; Gutiérrez et al., 2020).

In the acute phases of the emergency, the disease has forced government agencies to consider several preventive measures to control its spreading. In Italy, during the first wave of 2020 a national lockdown of about two months was imposed by the government to limit population mobility, provoking a reduction in urban travel and number of air flights. During the second wave started in fall 2020, differentiated strategies were implemented according to the “colours” of the regions based on multiple sanitary indicators by the Italian Ministry of Health. However, data are not easily accessible or clearly explained to the public, resulting in uncertainties and, sometimes, leading to protests from the regional government departments.

Notwithstanding the effectiveness of social distancing measures, the debate on the actual impact of travel limitation measures is very lively, both in the academic world and in public opinion. Public transport is a case in point, being its influence on the virus spreading highly debated (Tirachini and Cats, 2020).

Mobility restrictions, indeed, affect the economic conditions of both people and governments and are also responsible for a “segregation effect” of people with low income (Bonaccorsi et al., 2020). It is therefore important to quantify the effectiveness of various measures on the spread of the virus, to avoid overestimating the effects of health prevention that can generate various equally serious economic and social consequences.

This paper proposes an agent-based model to dynamically simulate the impact of mobility restrictions on the spreading of the COVID-19 at a national scale. The model proposed is new, since it reproduces a real case study, i.e. Italy, at the spatial scale of national regions. Besides it considers multiple data sources and *a-priori* parameters that can be related to the risk of spreading. To build the ABM, we drew inspiration from a previous study aimed at measuring an *a-priori* risk index for each of the 20 Italian regions based on an analytical model (Pluchino et al., 2021). The Authors showed that the geographic distribution of this index correlates with the available COVID-19 official data related to the pandemic spreading. Based on this, possible policy interventions have been suggested to tackle the virus spreading. Fazio et al. (forthcoming) proposes a first dynamical version of the model by Pluchino et al. (2021) to test their findings through an agent-based approach. They proposes an ABM as a tool to simulate any pandemic spreading based on respiratory diseases and tested it in the case of the COVID-19 spreading in Italy. This paper stems from Fazio et al. (forthcoming) by presenting the full ABM where a scenario analysis is also performed, differentiating for each region the measures to restrict mobility that might have been implemented to struggle the pandemic during the first COVID-19 wave.

The remainder of the paper is organised as follows. Section 2 includes an overview of similar studies, Section 3 presents the data and methods used to build the ABM, while section 4 introduces the case study and the related model steps. Section 5 presents and discusses the results with some policy implications. Section 6 concludes the paper.

2. Literature review

There is a growing literature dealing with the actual effects of mobility restrictions on the COVID-19 virus spreading. Parino et al. (2021) provided a spatial meta-population model to estimate the effectiveness of the so called non-pharmaceutical interventions (NPIs), such as social activity and mobility reduction imposition. Findings show that the efficacy of these policy measures could have entailed better benefits if imposed in the early phase of the outbreak. Zhou et al. (2020) built a mathematical model, fed by aggregate mobile phone data and infection data, to analyse the level of transmissibility of the virus in different mobility restrictions scenarios. Results show that a reduction of mobility around 20%–60% entailed a good effectiveness on controlling the infection spread. Carteni̇̀ et al. (2020) proposed a multiple linear regression model in order to estimate the consequences of the change in mobility habits of users. The Authors demonstrated that mobility habits, number of tests/day and other environmental variables are the ones that most influence the number of infections. Oka et al. (2021) came to similar conclusions, combining infection, death, and recovery data together with human mobility information. Gatto et al. (2020) conducted a mobility restrictions scenario analysis with the aim of quantifying the expected number of hospitalizations in Italy. Authors show that the absence of lockdown would have involved a huge increase in the number of hospitalized, while the increase would have been lower in case of more relaxed mobility restrictions. de Sousa et al. (2020), using a Kinetic Monte Carlo model, estimated the risk associated to short and long lockdown, concluding that the latter did not affect the number of infected contrary to what one would expect. Other studies about USA and Chinese cases analysed huge amounts of data and used statistical models to show the strong correlation of mobility restrictions on the virus spreading (Xiong et al., 2020; Badr et al., 2020; Kraemer et al., 2020).

However, the use of total number of cases to monitor the spread of the infection may lead to incorrect results, precisely because this value is highly conditioned by the actual number of tests carried out on the population. As a consequence, the quantification of the restrictions’ impact on the rate of infection is difficult, especially due to the biased data available.

In this respect, some authors focused on data of deaths, which are likely to be less affected by specific assumptions, and correlated them with mobile data, showing that mobility is responsible for more than 90% of the initial spreading in Italy and in France (Iacus et al., 2020).

Data analysis techniques usually play a big role to understand this type of phenomena; however, due to the rapid development of the pandemic, it is also important to have more general models capable of predicting the impact of different scenarios, independent on the available infection data. Simulation models could help to understand the possible impact of differentiated strategies (e.g. according to the geographical scale), and replicate the related scenarios in a disaggregated way.

In this respect, agent-based models (ABM) have many advantages, among them the possibility of simulating the behaviour of autonomous agents and the complex social interactions with other agents at a micro-scale level (Tzouras et al., 2021). Moreover, ABM is capable of including very rich data scenarios together with country-specific demographic data, and the possibility of simulating population mobility patterns (Cho et al., 2012; Le Pira et al., 2020; Calabrò et al., 2022).

A further advantage of using the ABM approach is the stochastic nature of the simulations, which allows to implement a component of randomness (Huppert and Katriel, 2013; Shi et al., 2014). ABM have been used to simulate virus spreading, drawing inspiration from the so-called SIR-based models and applying them to a dynamic simulation environment. Silva et al. (2020) proposed the so called COVID-ABS to simulate different scenarios (e.g. lockdown, use of face masks) and estimated their economic impact. Cuevas (2020) provided an ABM aiming at reproducing the transmission risks in facilities and performing different hypothetical scenarios. Both studies did not apply the model in a real case study but reproduced a synthetic population of a closed society. Lima and Atman (2021) presented an epidemiological model using an ABM to evaluate the spreading level at different percentage of mobility reductions. However, the Authors made the assumption of random walk for agents without referring to official mobility data. Kai et al. (2020) focused on the impact of universal masking through an ABM Monte Carlo. Their results suggest that a social distance measure without the adoption of mask wearing would have entailed an increase in the infection rate. Najmi et al. (2020) extended an existing activity-based model named SydneyGMA to replicate the case of Sydney by determining COVID-19-specific parameters and considering the interaction among agents resulting in a useful model at a city level. Mahmood et al. (2020) introduced an agent-based simulator of COVID-19 spreading, incorporated spatial, demography and epidemiology data. This model is configured as a decision tool that can be adopted by policy-makers for their specific context.

Notwithstanding the importance of these studies to analyse COVID-19 dynamics by reproducing its spreading at different scales, there is a general lack of comprehensive ABM capable of providing a decision-support tool for the design of strategic plans to contrast pandemics based on respiratory diseases. In this respect, this sanitary emergency highlighted the importance for countries of being equipped with an *a-priori* pandemic plan capable of suggesting efficient strategic solutions and intervening in advance to limit the negative effects. This paper is framed in this context and proposes an ABM that could be used for ex-ante evaluations of different scenarios at a large scale, i.e. the national one. The details about the data and methods used are presented in the following.

3. Data and methods

The rationale behind the use of ABM is to evaluate how the epidemic spread changes on the basis of different mobility restriction policies.

As previously mentioned, we drew inspiration from a previous study aimed at measuring an *a-priori* risk index for each of the 20 regions in Italy (Pluchino et al., 2021). The study showed that the geographic distribution of this index correlates at the regional scale with the available COVID-19 official data about the number of infected individuals, patients in intensive care and the number of deaths registered after the first epidemic wave in 2020. More in detail, the risk index was built combining the following indicators, extracted from data collected on a regional basis before the beginning of the pandemic: mean winter temperature (Wt), since low temperatures affect the spread and transmission of the virus; housing concentration (Hc), since urbanization of cities leads to a more threatening diseases diffusion; healthcare density (Hcd), as it was found the potential of hospitals to favour super-spreading events; population mobility (Pm), since this favour the interaction among people and the virus transmission; air pollution (Ap): the correlation between exposure to particulate pollution and the diffusion of COVID-19 is demonstrated by various studies; population over 60 (P_over60), considered more vulnerable to suffer virus effects. References and more detailed information can be found in Pluchino et al. (2021).

In the proposed ABM there are two types of agents: regions and individuals. Based on the actual population of each region, a proportional number of individuals is assigned, considering that each individual-agent is representative of a certain number of real individuals (with a scale of approximately 1:1000 based on the actual number of Italian population).

This approximation was made in order to avoid excessive simulation time arising from considering the real scale of the Italian population.

A description of the parameters affecting agents' behaviours is provided in section 4.1.

The construction of the model can be summarized as schematized in Fig. 1.

The ABM simulations were carried out through the NetLogo software, which is a multi-agent programmable environment for simulating and modelling complex systems by taking into account the evolution of the "agents" over time (Wilensky, 1999).

In the following, the case study of Italy is presented more in detail together with a description of the related model's phases.

4. Case study

The case study analysed in this work is related to Italy and its 20 administrative regions. Italy was the first European country in which the virus appeared, although the dynamics of spread and the date of the first infection remain uncertain. The first confirmed cases of contagion date back to 2020, January 23rd, when two tourists from China were tested positive for the virus in Rome. The first two official outbreaks of COVID-19 infections with positive cases of Italian citizens were reported later on February 21st, in Lombardy

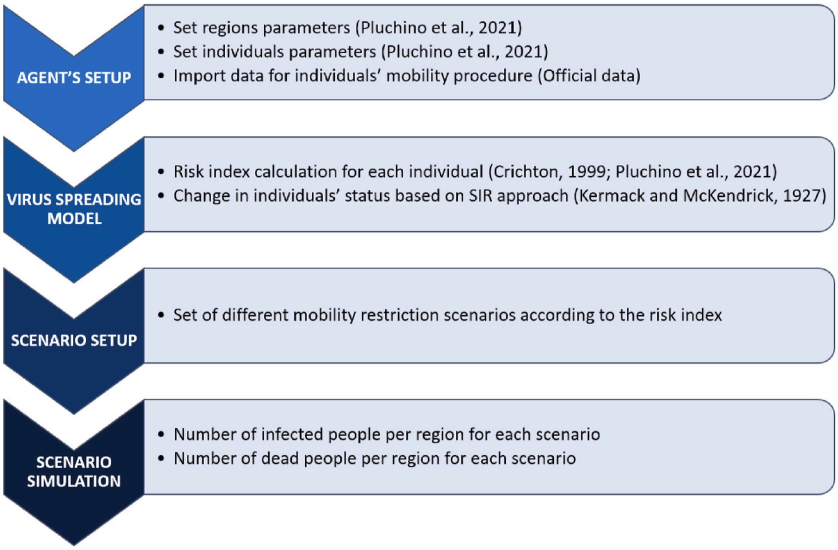

Fig. 1. ABM steps.

and Veneto.[1] Since then, the infection has spread throughout Italy with varying intensity. Nevertheless, several studies have shown that there were actually cases even before (Apolone et al., 2020; Valenti et al., 2020). On March 7th a government measure imposed some travel limitations. On March 11th, the restrictive measures were converted into a national lockdown, with a "stay-at-home" order allowing travelling only for essential services or urgent reasons, with the aim of stopping the spread of the virus. This national lockdown of about two months has provoked a tough reduction both in short and long distance travelling.

Fig. 2a shows statistics on the number of daily cases in Italy. As can be seen, the trend increases starting from March and it seems to have a surge in the second wave starting from October 2020. The first trend is justified by the difficulty to accurately detect the actual number of infected (Tradigo et al., 2020). Subsequently, with the growth in the number of tests, the share of recorded infected people has gradually increased. Nevertheless, uncertainties on the actual number of cases still remain, due to the biased data available on the contagion rate.

In October 2020, the World Health Organization (WHO) stated that 10 percent of the global world population was infected with the virus.[2] This leads to the belief that also in Italy the number of infected was actually much higher than reported by official data sources, touching the millions of infected. This number is also comparable with the average annual number of seasonal flu cases.[3] The number of daily deaths (Fig. 2b) has instead the same order of magnitude in both waves.

The absence of reliable data on the number of infections did not allow to have clear information on the actual effects of the restrictions imposed in the first COVID-19 wave on the virus spreading.

Based on these premises, we developed an ABM able to reproduce a contagion rate which matches WHO statistics (resulting in a higher number of total cases) and the differentiation of infections between the Italian regions visible from the data collected by the

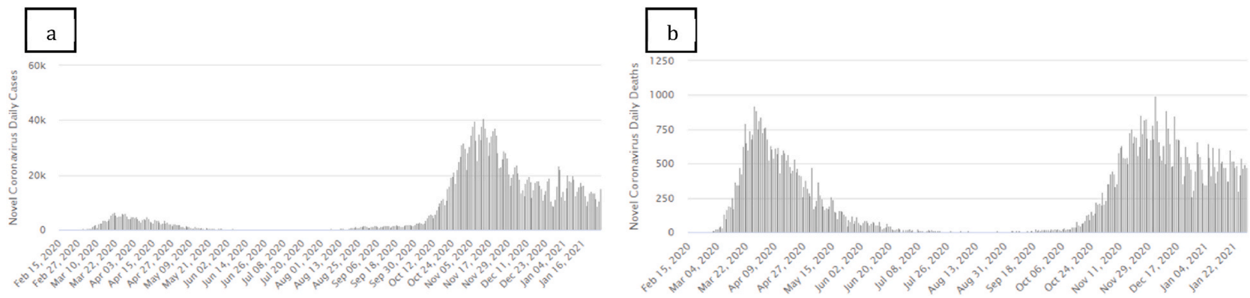

Fig. 2. Daily new cases (a); daily deaths (b) in Italy (source: https://www.worldometers.info/coronavirus/country/italy/).

[1] https://lab24.ilsole24ore.com/storia-coronavirus/.
[2] https://www.cnbc.com/2020/10/05/who-10percent-of-worlds-people-may-have-been-infected-with-virus-.html.
[3] https://www.epicentro.iss.it/influenza/stagione-2019-2020-primo-bilancio.

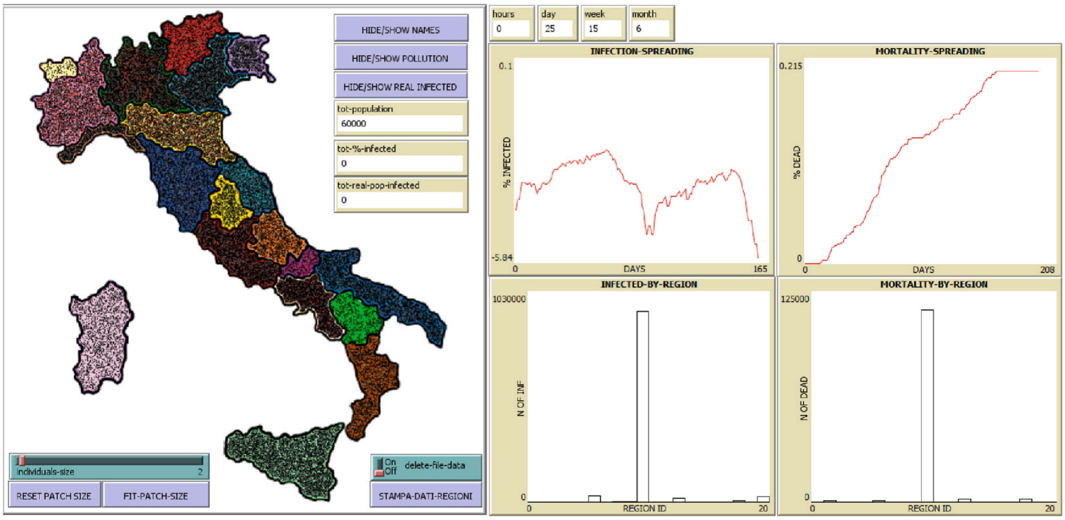

Fig. 3. Simulation environment.

Italian Ministry of Health. In this paper we will use the model to simulate different mobility restriction scenarios and evaluate the related impacts during the first epidemic wave in 2020. As shown in Fig. 3, the realistic geographical distribution of representative agents on the Italian territory allows to simulate the population mobility either in absence or in presence of restrictions, evaluating in real-time the virus diffusion and the corresponding effects in terms of infections and mortality.

Thanks to the results obtained, it will be possible to provide suggestions on mobility restrictions for an emergency plan that could be adapted not only for the case of COVID-19, but also for other similar pandemics.

The steps of the ABM and the selected scenarios are described in the following.

4.1. Model steps

4.1.1. Agents setup

In the setup phase all the parameters relating to both regions and individuals are set. Each agent r (region) is characterized by the following parameters: Wt, Hc, Hcd, Ap, Pm and P_over60. Each agent i (representing individuals) inherits the first 5 parameters from its home region and is classified in an age-group depending on the percentage of P_over60.

The dynamics of the model is given by the changes in people mobility through the Pm parameter (Pm_reduction), which are evaluated for each agent r and different time windows, according to mobility restriction.

For the mobility procedure, reference was made from an Italian mobility report which contains an overview of the mobility habits of people in Italy ("16° Rapporto sulla mobilità degli italiani", source: ISFORT[4]). This report provides the percentage distribution of trips for four classes of distance from 2 km to over 50 km (Fig. 4). Individual-agents in the model move according to the assigned mobility index (Pluchino et al., 2021) multiplied by the probability of making a trip belonging to these distances' classes. Trips over 50 km are considered as done by plane. For airline mobility, authors referred to a dataset containing Origin-Destination matrix of airline travel for each region (source: ENAC, 2019 [5]).

The model is capable of dynamically reproduce mobility restrictions by using three main datasets that provide the reduction of air flights from March 7th until June 25th, daily mobility radius, and number of trips. OpenData are used to gather information about mobility decrease considering, in particular, the reduction of air flights from 2019 to 2020 and the reduction of the radius and number of overall trips (references are reported in Table 1).

Table 1 summarizes agents' parameters (P). Each parameter has been normalized between 0 and 1, as in Pluchino et al. (2021).

4.1.2. Virus spreading model

For the calculation of risk index (RI) authors referred to the Crichton's Risk Triangle (Crichton, D., 1999), which evaluates RI as a function of three parameters: hazard, vulnerability, and exposure. (i) Hazard takes into consideration those factors that can intervene in the spread of the infection; (ii) Vulnerability is a measure of probability that an individual suffers a health damage due to infection; (iii) Exposure refers to the number of exposed people.

In the study of Pluchino et al. (2021), the RI is calculated for each region r as a floating-point variable between 0 and 1 and is obtained as:

[4] https://www.isfort.it/progetti/16-rapporto-sulla-mobilita-degli-italiani-audimob/.

[5] https://www.google.com/search?q=enac+dati+traffico+2019/.

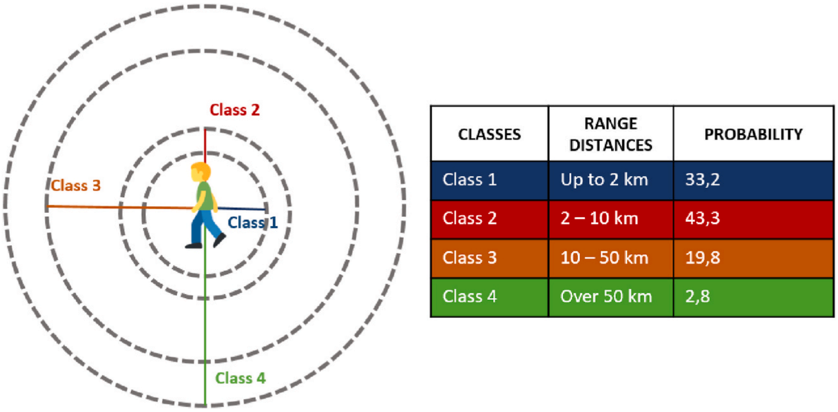

Fig. 4. Scheme of distances classes.

Table 1
Summary of agents parameters.

P	Description and unit	Source	Type
Wt	Average winter temperature (°C)	Italian Ministry of Agriculture (2016–2017)	Fixed for each region
Hc	Ratio between the total number of houses and the number of houses classified as “detached houses"	Italian Ministry of Economic Policy Planning and Coordination (2011)	Fixed for each region
Hcd	Number of hospital beds per inhabitant	Italian Ministry of Health (2019)	Fixed for each region
Ap	Exposure to concentrations of particulate matter (PM)	WHO (2016)	Fixed for each region
Pm	Ratio between the sum of commuting flows (incoming and outgoing) for a region and the population employed in the region.	Italian Ministry of Economic Policy Planning and Coordination (2011)	Fixed for each region
Pm_reduction	1. reduction of air flights (%); 2. reduction of the dimension of the daily mobility radius (%); 3. reduction of the number of trips (%);	1. EUROCONTROL 2. Covid19mm.github: first report 3. Google: covid19-mobility	Dynamic time windows
P_over60	Fraction of population over 60	ISTAT (2011)	Fixed for each region

$$RI = HAZARD \bullet VULNERABILITY \bullet EXPOSURE \tag{1}$$

Hazard, vulnerability and exposure are also floating-point variables between 0 and 1, in turn calculated as follows:

$$HAZARD = 1/3 \bullet Hc + 1/3 \bullet Hcd + 1/3 \bullet Pm \tag{2}$$

$$VULNERABILITY = 1/3 \bullet Wt + 1/3 \bullet Ap + 1/3\ P\_over60 \tag{3}$$

$$EXPOSURE = \text{population of each region} \tag{4}$$

In the ABM model authors propose a dynamic version of RI by referring it to each individual-agents. In this respect the new risk index (ri) is calculated as follow:

$$ri = hazard \bullet vulnerability \tag{5}$$

$$hazard = 1/3 \bullet Hc + 1/3 \bullet Hcd \tag{6}$$

$$vulnerability = 1/3 \bullet Wt + 1/3 \bullet Ap \tag{7}$$

The model provides a disaggregate version of RI in which the Pm, P-over60 and exposure component are specific characteristics referred to each agent i and therefore are not considered for the direct calculation of the risk index.

In order to simulate the total Italian population (about 59433744 individuals at the beginning of 2020) we adopt 60000 agents i, each one representing 991 real individuals, then we distribute them at random inside the territory of each region (see the black dots in Fig. 2), proportionally to the respective inhabitants.

RI is therefore assigned to each region and also characterizes each individual living in that region, as explained below. Official data show that 95% of people died in Italy due to COVID-19 were aged over-60.[6] For this reason, for the calculation of RI, a distinction was made between under-60 and over-60 years old, increasing the probability of being exposed for the latter category.

By combining the RI with the mean infection duration, the model determines the status associated to each individual on the basis of a SIR-based approach (Kermack and McKendrick, 1927): susceptible, infected, isolated (or not isolated), immune and dead. The mean infection duration, based on official data (Italian Ministry of Health[7]), is considered equal to 10 days. Individual-agents change their status according to the procedure summarized in the following flowchart below (Fig. 5) and hereby described. The simulation starts with two agents with the status "infected" which represent the "zero patients". All the other individual-agents start from a status called "susceptible". Once the simulation starts and the individuals begin to travel according to the assigned mobility index, if a "susceptible" individual encounters an "infected" one, in an infection radius of about 7 km (Covid19mm.github: first report), it will have a probability to contract the virus based on the product between hazard and virulence. If the result of this product is more than a random floating number between 0 and 1 (random-float 1 in Fig. 5), individuals will change their status into "infected". After getting infected, the individual is assigned with a probability of being symptomatic (≤10%) or asymptomatic (≥90%),[8] that turns him respectively into the new status or "isolated" and "not isolated". Finally, after the mean infection duration, the individual dies or recovers from the infection, by comparing the product between vulnerability and lethality with a random floating number between 0 and 1, assuming respectively "dead" or "immune" status.

While hazard and vulnerability are parameters directly linked to each individual, virulence and lethality are related to the characteristic of the virus. Virulence, which corresponds to the contagiousness of the virus, is a fixed parameter. Its value has been calculated through a calibration procedure by reproducing different scenarios and varying virulence until obtaining results comparable to the real data in terms of number of deaths. Also for the lethality, which correspond to the mortality level of the virus, reference was made to real data.

Due to the data uncertainty, lethality value varies according to a Gaussian probability distribution with mean 0.02 and standard deviation 0.01, i.e. lethality oscillates around 2% (Russell et al., 2020).

4.1.3. Choice of analysis scenarios

According to policy suggestions by Pluchino et al. (2021), the following scenarios have been tested:

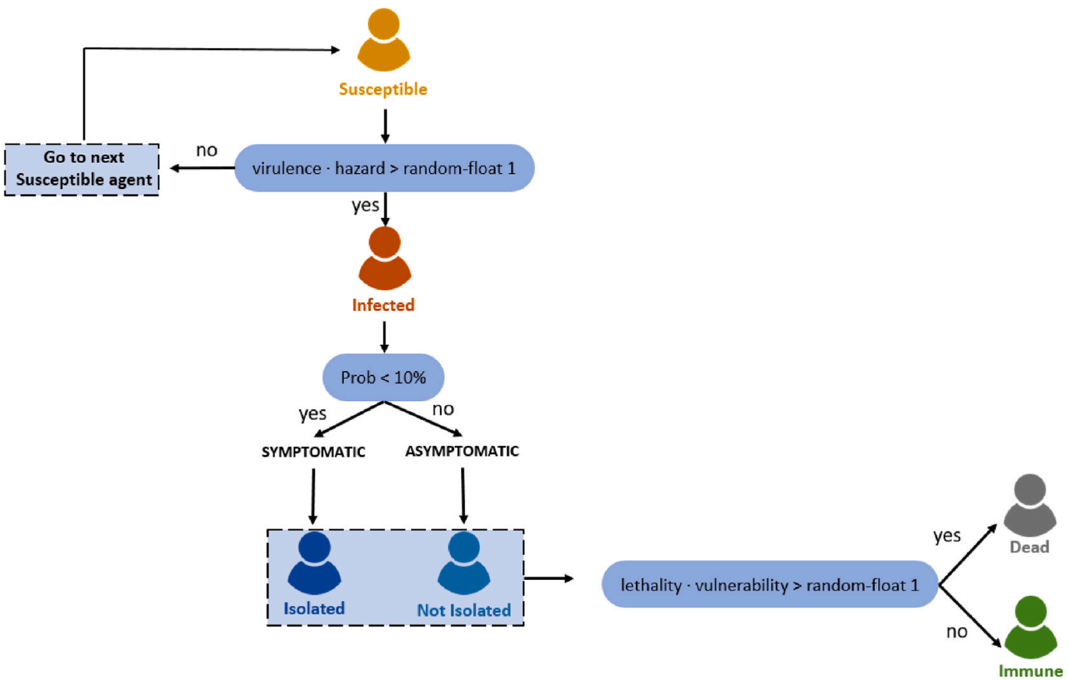

Fig. 5. Individual's status change procedure flowchart.

[6] https://www.epicentro.iss.it/coronavirus/sars-cov-2-decessi-italia.
[7] http://www.salute.gov.it/portale/nuovocoronavirus/dettaglioNotizieNuovoCoronavirus.jsp?lingua=italiano&id=5117.
[8] https://www.istat.it/it/archivio/246156.

- *Status Quo*: Same total mobility restrictions for all regions;
- *Scenario N1*: No mobility restrictions at all (RI = 1 for all regions);
- *Scenario S1*: Total mobility restrictions for all the regions (RI = 1 for all regions);
- Different mobility restrictions according to 3 zones based on the values of the following parameters (Table 2, Table 3 and Fig. 6):
  o mobility index (*Scenario M*);
  o hazard (*Scenario H*);
  o vulnerability (*Scenario V*);
  o risk index (*Scenario RI*).

More details on how these parameters were calculated can be found in Pluchino et al. (2021).

4.1.4. Scenario simulation

Following the real case study, the analysis of different scenarios has the same starting date as the governmental restriction introduced in Italy (i.e. March 7th, 2020). December 28th, 2019 was chosen as the starting pandemic date for all scenario, due to the uncertainty of the beginning of the infection in the country (Apolone et al., 2020; Valenti et al., 2020).

The two "zero patients" are in Lombardy and Lazio, regions where the first cases of COVID-19 occurred and also those where hub airports are present; hence they were considered the regions with more connections to other countries.

The output data of the simulation, calculated on June 25th, 2020 (after the end of the first epidemic wave), are the following:

- Number of infected people for each region;
- Number of dead people for each region.

Each scenario was simulated 5 times and the results were averaged to have a statistics of the events. Computing simulation time for

Table 2
Zone classification according to mobility index, hazard, vulnerability and risk index.

Regions	mobility index	Zone	hazard	Zone	vulnerability	Zon e	risk index	Zone
Abruzzo	0.15	1	0.33	1	0.06	1	0.04	1
Basilicata	0.03	1	0.23	1	0.01	1	0.01	1
Calabria	0.37	2	0.37	2	0.05	1	0.03	1
Campania	0.24	1	0.26	1	0.25	2	0.11	2
Emilia Romagna	0.81	3	0.69	3	0.23	2	0.27	2
Friuli Venezia Giulia	0.81	3	0.77	3	0.07	1	0.09	1
Lazio	0.53	2	0.50	2	0.23	2	0.19	2
Liguria	0.48	2	0.58	2	0.08	1	0.08	1
Lombardia	1.00	3	0.94	3	0.62	3	1.00	3
Marche	0.60	2	0.33	1	0.07	1	0.04	1
Molise	0.00	1	0.44	2	0.01	1	0.01	1
Piemonte	0.59	2	0.58	2	0.29	2	0.29	2
Puglia	0.29	1	0.45	2	0.11	2	0.09	1
Sardegna	0.29	1	0.60	2	0.04	1	0.04	1
Sicilia	0.54	2	0.53	2	0.09	1	0.08	1
Toscana	0.74	3	0.46	2	0.17	2	0.14	2
Trentino Alto Adige	0.66	2	0.74	3	0.04	1	0.05	1
Umbria	0.55	2	0.42	2	0.04	1	0.03	1
Valle d'Aosta	0.64	2	0.73	3	0.01	1	0.01	1
Veneto	0.95	3	0.69	3	0.27	2	0.32	2

Table 3
Characterization for zone-based scenarios.

Risk index zone	Parameter	ZONE 1	ZONE 2	ZONE 3
Scenario M	mobility index	No mobility restriction	50% of mobility restriction	Total mobility restriction
Scenario H	hazard			
Scenario V	vulnerability			
Scenario RI	risk index			

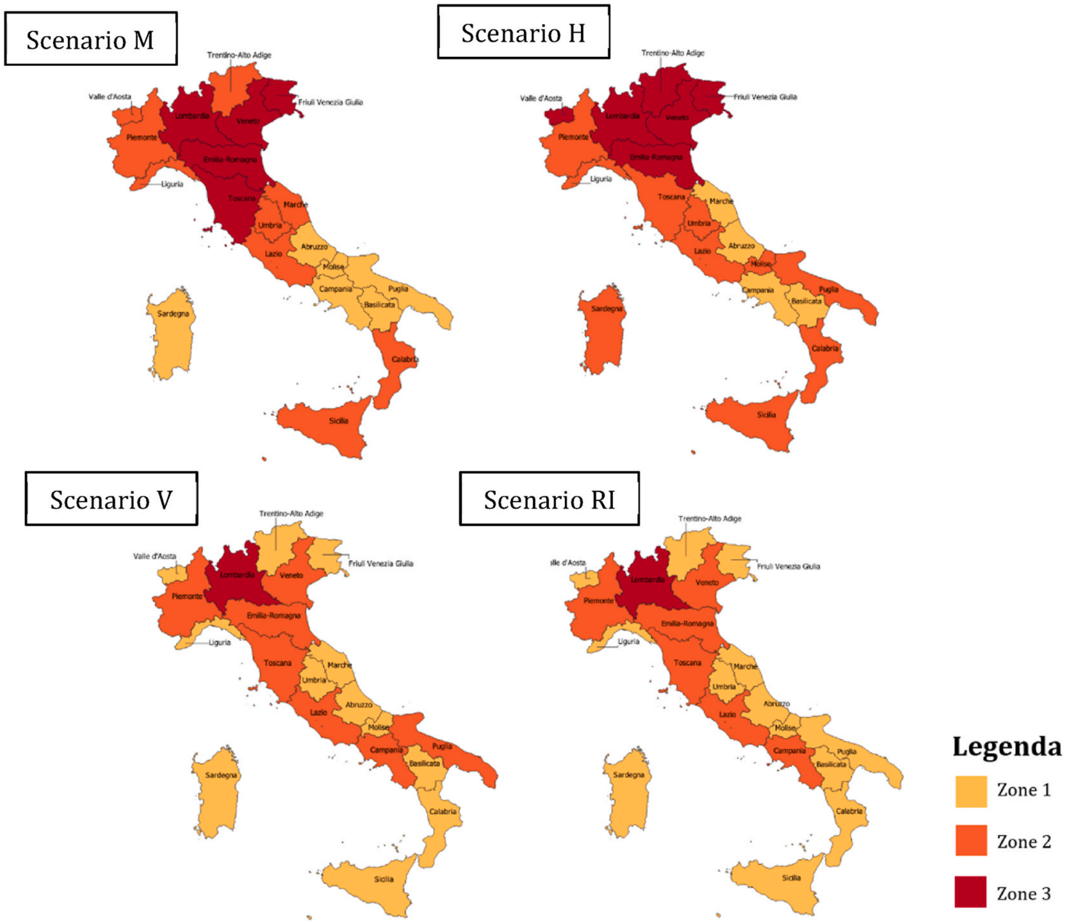

Fig. 6. Classification in three zones, with increasing mobility restrictions, for scenarios defined in Table 3.

each scenario assumes reasonable values (about 20 min).

5. Results and discussion

5.1. Results

In the following, results showed in Fig. 7 and Fig. 8 will be presented and discussed.

In the first rows of these figures, a comparison will be made between the *status quo* (a scenario assuming the national lockdown adopted by the Italian Government during the first epidemic wave) and the real COVID-19 data concerning, respectively, the cumulated number of infected and the cumulated number of deaths. It is worth of notice that the order of magnitude for the simulated infection cases substantially differs from that one of official data, while it is the same for the number of deaths. As already anticipated, the absence of an adequate tests sampling, especially in the first wave, has led to an unreliable number of infected recorded by the official institutions. Through the simulations it has been verified that, in order to obtain a comparable total number of deaths (about 39,000 simulated against the 35,000 reals, from December 28th, 2019, until June 25th, 2020), millions of circulating infected individuals would be necessary. This finding confirms the hypothesis, already discussed in Section 4, that the official data about infected was heavily underestimated. However, in terms of relative distribution of cases in the various regions, the comparison of the two chromatic maps in the first row of Fig. 7 is quite good. The same holds also for the analogous comparison in Fig. 8, where the simulated distribution of deaths among the Italian territories correctly identifies the northern regions as the most damaged, as in reality. The apparent discrepancy concerning the central and southern regions, which in the *status quo* simulation registered fewer deaths than in the real cases, can be explained recalling that the main approximation of the present model lies on the fact that each agent is representative of about 1000 individuals. Therefore, the epidemic behaviour in regions with less than 1000 deaths cannot be properly captured by the simulations, which return a null result.

The next step is to compare the *status quo* scenario with other alternative zone-based scenarios, i.e. M, H, V and RI. Looking again at Figs. 7 and 8, second and third rows, it can be noticed the expected increase in the number of infected and dead people due to the lower

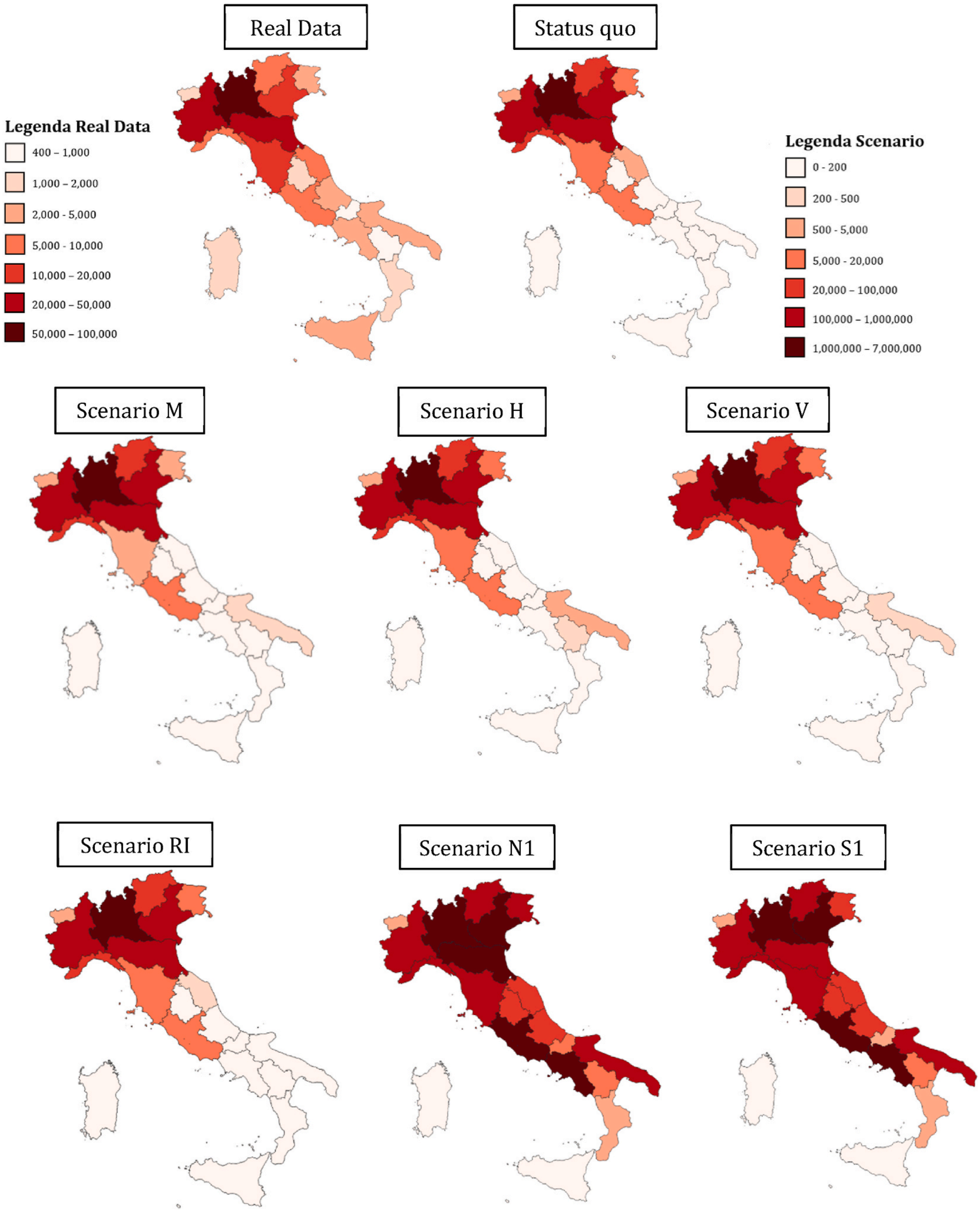

Fig. 7. Distribution of number of infected for each scenario.

restrictions. As summarized in Table 4, the increase is about 20% on average for the total number of infected and 25% for the total number of deaths for the whole Italian territory. The increase for the most damaged region, i.e. Lombardy, goes from 20% to 31% for both infected and dead people. These findings are in line with other research studies. Gatto et al. (2020) simulated a scenario in which the duration of mobility restrictions during the first phase in Italy only lasted one month. In comparison with the *status quo*, the considered scenario entailed only a small increase in terms of hospitalization, comparable to the increase in the number of infected obtained in our model. Lima and Atman (2021) observed an effective reduction of infection rate with the flattening of the infection curve for a percentage of mobility reduction of 70%–90%, less than a 100% of reduction which corresponds to a total lockdown. Similarly, de Sousa et al. (2020) demonstrated that a total lockdown policy did not have much effect on reducing the peak of the infection curve. However, even if solutions with partial lockdowns are of course preferable from the socio-economic point of view, the increment in terms of loss of human life is not negligible with respect to the total lockdown and should be carefully evaluated. On the

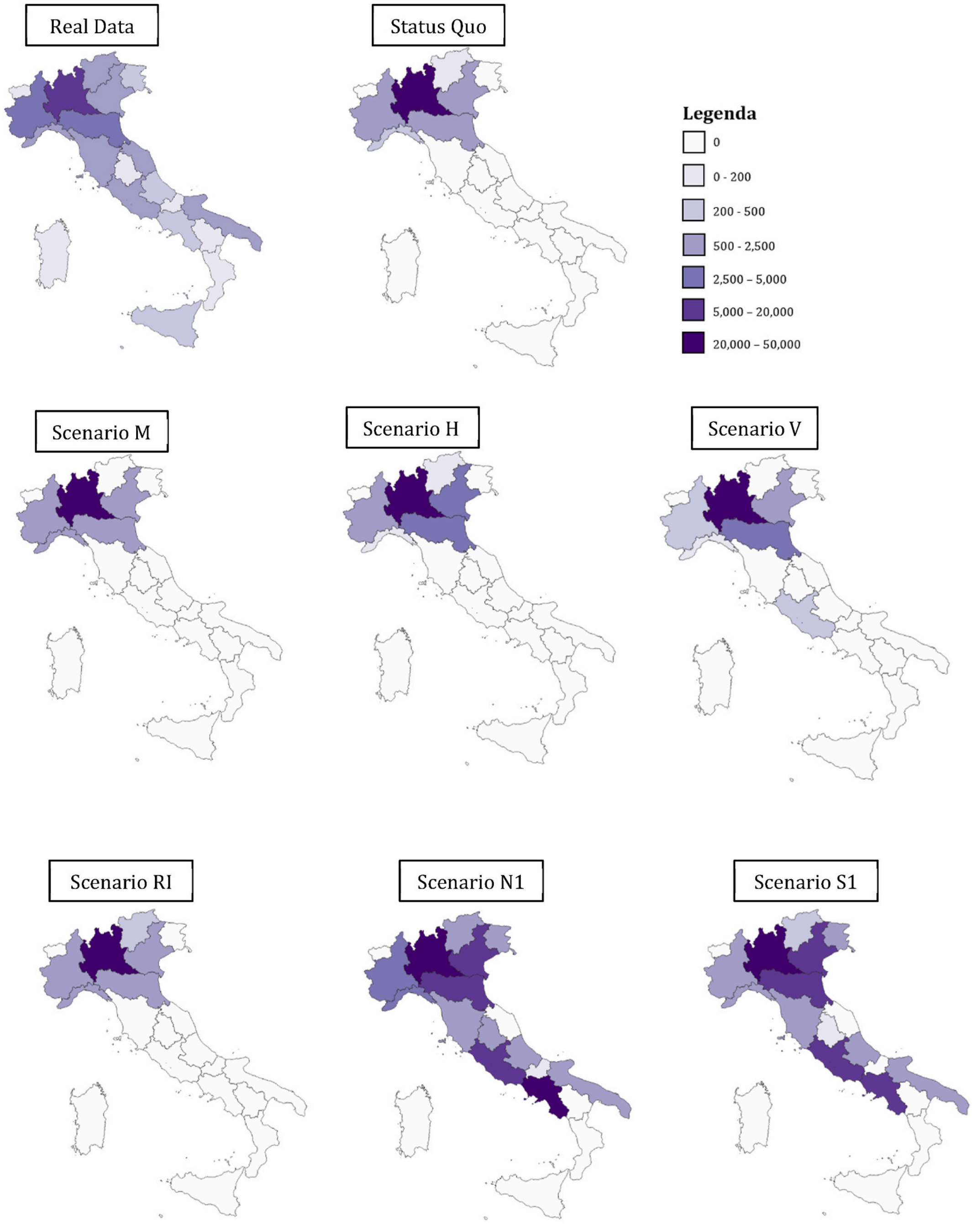

Fig. 8. Distribution of number of deaths for each scenario.

other hand, there are no relevant differences in the results of the four indicator-based scenarios. Therefore, the RI scenario can be considered as the best solution, since is the one implying less restrictions, i.e. fewer regions in lockdown.

Pluchino et al. (2021) already demonstrated the effectiveness of RI as a good indicator of virus spreading and consequences on the population, by correlating its regional values with real data of the first wave of the pandemic. Here, we can try to support this result by simulating two new scenarios with RI = 1 for all regions, i.e. with the same *a-priori* risk for the whole territory, and showing that the results are not compatible with real data. Scenario N1 simulates virus spreading in absence of lockdown while scenario S1 simulates the same national lockdown of the *status quo*. As expected, a huge increase in the number of infected and deaths (more than 100%) with respect to the simulated *status quo* is observed, particularly in scenario N1. Also Gatto et al. (2020) simulated a scenario without lockdown, obtaining similar results, i.e. a very high increase in hospitalization. This suggests that the consequences in terms of infected and deaths would have been much worse if *a-priori* conditions would have no influence on virus spreading. Moreover, in these

Table 4
Summary of the results obtained for each scenario.

SCENARIO	Number of region for each zone			% increment of infected with respect to SQ		% increment of deaths with respect to SQ	
	ZONE 1	ZONE 2	ZONE 3	Total	Lombardy	Total	Lombardy
M	6	9	5	+22%	**+30%**	+28%	**+31%**
H	4	**10**	6	+17%	+25%	+30%	+30%
V	12	7	1	+22%	**+30%**	+18%	+20%
RI	13	6	1	+21%	+28%	+26%	+30%
N1	**20**	0	0	**+123%**	+1%	**+187%**	**+31%**
S1	0	0	**20**	+106%	−12%	+156%	+18%

scenarios damages would be more uniformly distributed over the Italian territory than in reality, without substantial differences between northern and central-southern regions.

5.1.1. Policy implications and discussion

In terms of policy implications, the main result is that differentiated mobility restrictions for the different regions are a suitable solution to limit virus spreading while reducing the overall impact on the economy. This is in line with the policies adopted by the national Government for the second wave that defined three zones (red, orange and yellow) based on multiple healthcare indicators, which depend both on the ability of each region to cope with the virus spreading, and real-time data based on a continuous monitoring. However, our model suggests solutions that could be applicable for any sanitary emergency, regardless of real-time data, which could be, as in this case, naturally biased. In this respect, the ABM could be used to set the initial mobility restrictions, which should be updated according to the dynamic conditions linked to the virus spreading.

In other words, the model could be considered a decision-support tool for any strategic plan to contrast pandemics based on respiratory diseases, allowing a classification of regions based on *a-priori* data that could be regularly updated to have an up-to-date risk assessment for each region and know in advance the impact of different mobility restrictions strategies. This is particularly important and needed, given the unpreparedness of different countries to cope with the virus and, in the case of Italy, the lively debate around the outdated pandemic plan.[9]

Moreover, since the model predicts the impact of the reduction of the radius of trips on the virus spreading, it could be also used to simulate targeted policies based on municipal, regional or national mobility. In the performed simulations, a lower radius for trips (i.e. short trips) reduces the risk of contagion because of a lower probability of getting in touch with other people, and this suggests that local policy-makers should guarantee adequate accessibility to essential services on short distances during pandemics and promote the use of sustainable transport modes to reach them, also in the view of the effects of pollution on the transmission of respiratory disease, proven also in the case of COVID-19 (Hensher, 2020; Gutiérrez et al., 2020).

To sum up, from a policy-maker point of view, in order to reduce the spread of a virus epidemic, it is possible to plan twofold policies, based on the parameters related to the risk index: (i) reducing the hazard (protection policy) by adopting different mobility restrictions, according to the simulation results that dynamically provide the risk level of a region over time; (ii) reducing vulnerability (prevention policy) by promoting forms of sustainable mobility and compact city (e.g. 15-minutes city), capable of reducing the environmental impact and fostering shorter trips. In this respect, the Italian government has been following this path, implementing national policies for the purchase of non-polluting vehicles (e.g. "Buono mobilità"), and promoting the construction of infrastructures dedicated to active mobility[10, 11].

6. Conclusion

In this paper, an ABM is presented to dynamically simulate the impact of mobility restrictions during COVID-19 pandemics in Italy. Different mobility limitation scenarios have been simulated with the aim of suggesting possible policy measure to limit the virus spreading. The scenario construction is based on the assignment of different mobility restrictions: no mobility restrictions at all, total mobility restrictions or different mobility restriction corresponding to 3 zones according to different parameters (i.e. M, H, V and RI). The main results show that assigning an *a priori* regional risk allows to adopt policies of localized restrictions that maintain almost the same effectiveness as a complete closure, allowing the opening of a greater number of economic activities and a greater mobility. In the second wave, the Italian government decided a similar zonation, classifying Italian regions into three risk areas based on the progressive gravity of health emergency.

These government measures consider only sanitary parameters and are suitable for real-time management of the health emergency.

However, at the beginning of the pandemic, the adoption of an adequate pandemic plan could have led to less drastic economic consequences (Haug et al., 2020).

[9] https://www.theguardian.com/world/2020/aug/13/italy-pandemic-plan-was-old-and-inadequate-covid-report-finds.
[10] https://www.gazzetta.it/bici/03-11-2020/milano-50-chilometri-nuove-piste-ciclabili-l-obiettivo-2020-390550946007.shtml.
[11] https://www.gazzettaufficiale.it/atto/serie_generale/caricaDettaglioAtto/originario?atto.dataPubblicazioneGazzetta=2020-09-05&atto.codiceRedazionale=20A04737&elenco30giorni=false.

In this respect, the model proposed in this paper aims at providing useful suggestions to contrast epidemic emergency in the context of a preliminary strategic plan. The reproducibility of the model and its scalability to different territorial contexts makes it a tool able to provide valuable information for government agencies to undertake the proper interventions in the event of a pandemic diffusion. In this respect, as future research, it should be tested in other contexts where the virus spreading followed different patterns. Finally, the ABM can also be adapted to other health emergencies caused by respiratory diseases. Notwithstanding the potential of ABM for simulating virus spreading, there are some limitations. Once is related to the approximation of 1 agent corresponding to almost 1000 real individuals, making it difficult to recreate the early periods of the pandemic when the number of infected/deaths was still in the hundreds. Another limitation is linked to the mobility analysis. In this model agents move according to classes of distance, but a differentiation in terms of modes of transport has not been implemented (excluding very long distance trips which are considered as by plane). In this respect, future research might include the use of different modes of transport and assign to each of them a risk of infections, considering that collective modes have been considered riskier than individual ones, due to their potential crowding (e.g. see Barbieri et al., 2021). This would be relevant if one adopts a higher level of details, e.g. by focusing on the urban scale instead of the national one. Moreover, a dynamic of vaccine administration could be implemented, with the aim of evaluating its effectiveness together with the policies of restrictions on mobility.

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